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A Markov Chain Prediction Model on a Major Pair in the Currency Market

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Abstract

The markov chain prediction model is a type of stochastic model and very useful in predicting prices of stocks and exchange rate with outcomes which appear to be random in nature due to many factors that influences the price movement. The uncertainty in the price of the stocks and exchange rates arose from the many factors which includes the economy of the region, financial and economic news of other regions, exchange rates, etc. This study try to predict the price action using the markov chain prediction model applied to the difference in the typical price and closing price of the daily exchange rates. The model is applied to the European Euros and United States Dollar (EURUSD) currency pair in the currency market. The model works well with the Euros and United States Dollar (EURUSD).

1. Introduction

In 1906, Audrey Markov first introduced the Markov chain and he explained Markov Chains as a stochastic process containing random variables , transitioning from one state to another depending on certain assumptions and definite probabilistic rules. These random variables transition from one state to another state based on the mathematical property called Markov property.

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A Markov model is then defined as a stochastic model that models random variables in a way that the variables follow the Markov property.
A stock market, share market or equity market is the aggregation of buyers and sellers of stocks (also called shares), which represents ownership claims on businesses. They may include securities listed on a public stock exchange, as well as stock that is only traded privately. A stock exchange is an exchange where stock brokers and traders can buy and sell shares of stocks, bonds and other securities.
The international currency market is the largest financial market in the world, with an average daily trading volume of $5 trillion. In this market, transactions do not occur on a single exchange, but in a global computer network of large banks and brokers from around the world. The currency market, or foreign exchange market ("forex"), was created to facilitate the exchange of currency that becomes necessary as the result of foreign trade. That is, when an entity in one country sells something to an entity in another country, the seller earns that foreign currency.
One of the relationships between stock market and currency market is that when a domestic equity market rises, confidence in that specific country grows as well, leading to an inflow of funds from foreign investors. This tends to create a demand for the domestic currency, causing it to rally versus other foreign currencies. On the flip side, when a domestic equity market performs terribly, confidence falters, causing investors to convert their invested funds back into their own local currencies. It is therefore imperative to formulate models that can predict the exchange rates. The rest of this paper is arranged as follows; the section 2 discusses the markov chain prediction model, the methodology, model formulation technique and data collection techniques used in the study, section 3 explores the model formulated to predict closing prices for the pair considered and gives a detailed discussion on the results obtained, the last section gives the conclusion as well as recommendations for further work.

2. Markov Chain Prediction Model

In this study, a first order Markov Chain is used and is formulated thus: Let $Pr\{A\}$ denote the probability that an event A is going to happen, and given the equation,

$$\begin{aligned} & Pr\{S_P(t_{h+1}) = Sj \| S_P(t_h) = Si_h, S_P(t_{h-1}) = Si_{h-1}, \cdots, S_P(t_1) = Si_1\} \\ (1) \quad & Pr\{S_P(t_{h+1}) = Sj \| S_P(t_h) = Si_h \\ & \text{for each } j, i_1, i_2, \cdots, i_h \in \{1, \cdots, N\} \end{aligned}$$

it states that in a first order markov chain, the probability that $S_P(t_{h+1})$ at t_{h+1} is Sj, given the state of the process at t_h, does not depend on the previous history of the process. Therefore we can define the probability of the state at t_{h+1} is Sj , given that the state at t_h is Si below;

$$Pij = Pr\{S_P(t_{h+1}) = Sj \| S_P(t_h) = Si\} \tag{2}$$

The transition probability matrix is then given as;

$$Pij = \begin{bmatrix} P11 & P12 & P13 & P14 & \cdots & P1N \\ P21 & P22 & P23 & P24 & \cdots & P2N \\ P31 & P32 & P33 & P34 & \cdots & P3N \\ P41 & P42 & P43 & P44 & \cdots & P4N \\ & & \vdots & \vdots & \vdots & \\ PN1 & PN2 & PN3 & PN4 & \cdots & PNN \end{bmatrix} \tag{3}$$

In this paper, we will restrict the transition matrix to a 2×2 matrix denoted as

$$Pij = \begin{bmatrix} P11 & P12 \\ P21 & P22 \end{bmatrix} \tag{4}$$

Denote the initial state probability vector as $\mathcal{S}_0(t_h)$, whose elements are all zero but the element corresponding to the state Si_h the process is at time t_h, which is set to equal to 1. We therefore define the state probabilities vector as :

$$\mathcal{S}(t_h) = [\mathcal{S}_1(t_h), \mathcal{S}_2(t_h), \cdots, \mathcal{S}_N(t_h)] \tag{5}$$

where $\mathcal{S}_i(t_h) = Pr\{S_P(t_h) = Si\}$, and we have the state probabilities vector at time t_{h+1} as follows:

$$\mathcal{S}(t_{h+1}) = \mathcal{S}(t_h) \cdot P(t_h) \tag{6}$$

where $P(t_h)$ is the probability transition matrix at time t_h.

2.1. **Research design.** This study focuses on the European Euros and United States Dollar (EURUSD) pair. The EURUSD is one of the major currency pair and one of the most traded pair. The period considered is a period of 77 days which span across three (3) months from August to October 2019.

2.2. **Data collection method.** All historical data used here were extracted from the MetaTrader 5 application of the Roboforex broker. It is a highly recognized international broker, therefore the prices obtained are authentic.

2.3. **Data Analysis method.** In financial trading, typical price T_t (sometimes called the pivot point) refers to the arithmetic average of the high, low, and closing prices for a given period.

$$T_t = \frac{H + L + C}{3} \tag{7}$$

where H is the high for the day, L is the low for the day, and C is the close price for the day, given that the period considered is a period of one day.

After collecting all the daily closing prices of the period considered, and the typical prices have been calculated, we then find the difference between the closing price and the typical price. This difference then serves as the basis for our Markov chain prediction model. In this work, we considered a 2 state Markov process, namely Bear or Bull. Bear is represented by state S1 and Bull is represented by state S2. The probability of a stagnant market is very low and hence almost negligible and won't be considered in this paper.

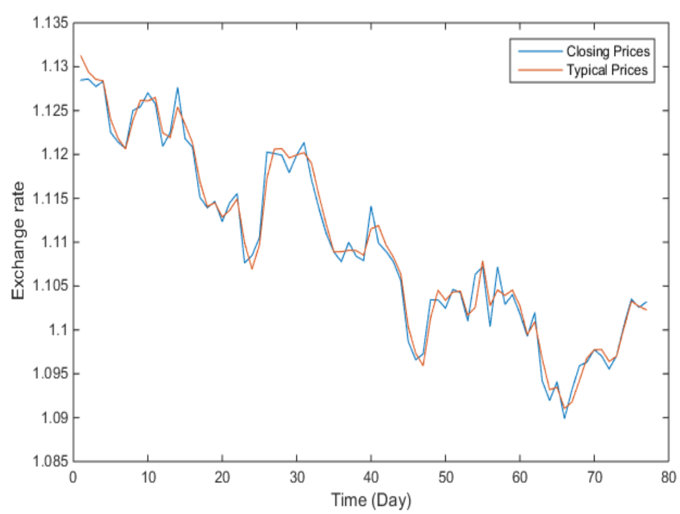
3. Application

The application of the prediction model on the difference of the typical price and the closing price are be carried out in this section. In section 2 above, we discussed the method of analysis as the difference of the prices and the basis of the transition. In this section, we will also give graphical and tabular representations to illustrate the analysis method. The derived states are the differences between the values obtained when the closing prices are subtracted from the typical prices and they are divided in the following intervals:

$$\text{S1} = (-\infty, 0)$$

(8) $$\text{S2} = (0, \infty)$$

(9)



3.1. **Table of values.** From Table 1 below, we derive the following probability transition matrix;

$$Pij = \begin{bmatrix} 0.42857 & 0.57143 \\ 0.73529 & 0.26471 \end{bmatrix} \tag{10}$$

Given the initial state vector $(1, 0)$, the probabilities of the next two days after the period considered are $(0.42857, 0.57143)$ and $(0.60384, 0.39616)$. This shows that there is 0.57153 probability of the bullish market on the next day, and there is 0.60384 probability of a bearish market on the second day, given that state S1 signifies a bearish market and state S2 represents a bullish market.

3.2. **Discussion of Results.** For the first day, the prediction according to the Markov Chain prediction model is that the exchange rate in the EURUSD market will fall into state S2 with a probability of 0.57143. This means that the exchange rate will close with a difference that falls in the interval $(0, \infty)$. When we compare the prediction with the actual price of the day, 1.1124, we observed that a bullish market and hence the prediction is 100% accurate in the prediction as the state S2 has the higher probability. For the second day, the model in this study predicted 0.60384 probability of the market falling in state S1. This means that the expected rate of the day must be less than the previous day which is 1.1124. The actual closing price of the second day is 1.10718, showing that the prediction is also accurate for the second day and the market turned out to be bearish.

4. Conclusion and Recommendations

4.1. **Conclusion.** When we compare the results found in this research with past literature, we observed that the model presented here works perfectly well with the currency pair considered. We applied the Markov chain prediction model to predict the price action of a major pair in the currency market using the typical price of the daily exchange rate. With the derived results, it is concluded that the model can be used to predict the exchange rate. However, it should be used as a guide or supplement to traders existing method of analysis because the exchange rate is greatly influenced by a lot of factors.

4.2. **Recommendations.** We hereby recommend that the model be applied to other currency pairs, to determine which one it handles best. We also recommend that it should be applied to the weighted price of daily exchange rates and other time frames like the weekly and monthly exchange rates.

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TABLE 1. Table of values for EURUSD

Date	Closing Prices	Typical Prices	Typical - Closing	Differences	States
2019 7 1	1.1285	1.1312	0.0027433	0	S2
2019 7 2	1.1286	1.1294	0.00082333	-0.00192	S1
2019 7 3	1.1278	1.1286	0.00081667	-6.67E-06	S1
2019 7 4	1.1283	1.1284	4.67E-05	-0.00077	S1
2019 7 5	1.1225	1.124	0.0014867	0.00144	S2
2019 7 8	1.1214	1.1218	0.00043667	-0.00105	S1
2019 7 9	1.1207	1.1206	-7.67E-05	-0.00051333	S1
2019 7 10	1.125	1.1239	-0.00115	-0.0010733	S1
2019 7 11	1.1254	1.1262	0.00073333	0.0018833	S2
2019 7 12	1.127	1.1261	-0.00091	-0.0016433	S1
2019 7 15	1.1258	1.1265	0.00070667	0.0016167	S2
2019 7 16	1.1209	1.1225	0.00155	0.00084333	S2
2019 7 17	1.1225	1.1219	-0.00056	-0.00211	S1
2019 7 18	1.1277	1.1254	-0.00226	-0.0017	S1
2019 7 19	1.1218	1.1234	0.0016233	0.0038833	S2
2019 7 22	1.1208	1.1213	0.00048333	-0.00114	S1
2019 7 23	1.1151	1.1169	0.0017667	0.0012833	S2
2019 7 24	1.1139	1.1141	0.00013667	-0.00163	S1
2019 7 25	1.1146	1.1145	-0.00013333	-0.00027	S1
2019 7 26	1.1123	1.1129	0.00053667	0.00067	S2
2019 7 29	1.1145	1.1136	-0.00088	-0.0014167	S1
2019 7 30	1.1155	1.1149	-0.00059	0.00029	S2
2019 7 31	1.1076	1.1099	0.0023067	0.0028967	S2
2019 8 1	1.1085	1.1069	-0.00156	-0.0038667	S1
2019 8 2	1.1105	1.1097	-0.00081667	0.00074333	S2
2019 8 5	1.1203	1.1173	-0.00301	-0.0021933	S1
2019 8 6	1.1201	1.1206	0.00049667	0.0035067	S2
2019 8 7	1.1199	1.1207	0.00074333	0.00024667	S2
2019 8 8	1.1179	1.1196	0.0016967	0.00095333	S2
2019 8 9	1.1199	1.12	2.00E-05	-0.0016767	S1
2019 8 12	1.1214	1.1202	-0.00116	-0.00118	S1
2019 8 13	1.1171	1.119	0.0018567	0.0030167	S2
2019 8 14	1.1138	1.1153	0.0014867	-0.00037	S1
2019 8 15	1.1109	1.112	0.00104	-0.00044667	S1
2019 8 16	1.1089	1.1089	6.67E-06	-0.0010333	S1
2019 8 19	1.1078	1.1089	0.0011267	0.00112	S2
2019 8 20	1.11	1.1091	-0.00091333	-0.00204	S1
2019 8 21	1.1084	1.109	0.00064	0.0015533	S2
2019 8 22	1.1079	1.1085	0.00062	-2.00E-05	S1

Date	Closing Prices	Typical Prices	Typical - Closing	Differences	States
2019 8 23	1.1141	1.1115	-0.0025833	-0.0032033	S1
2019 8 26	1.1099	1.1119	0.00201	0.0045933	S2
2019 8 27	1.109	1.1097	0.00074	-0.00127	S1
2019 8 28	1.1078	1.1083	0.00051333	-0.00022667	S1
2019 8 29	1.1056	1.1064	0.00075333	0.00024	S2
2019 8 30	1.0987	1.1003	0.00167	0.00091667	S2
2019 9 2	1.0966	1.0973	0.00074333	-0.00092667	S1
2019 9 3	1.0973	1.0959	-0.00135	-0.0020933	S1
2019 9 4	1.1034	1.1014	-0.00207	-0.00072	S1
2019 9 5	1.1034	1.1045	0.0011033	0.0031733	S2
2019 9 6	1.1025	1.1034	0.00093333	-0.00017	S1
2019 9 9	1.1046	1.1043	-0.00029333	-0.0012267	S1
2019 9 10	1.1042	1.1044	0.00017333	0.00046667	S2
2019 9 11	1.101	1.1017	0.00068333	0.00051	S2
2019 9 12	1.1063	1.1026	-0.0037733	-0.0044567	S1
2019 9 13	1.1072	1.1079	0.00069333	0.0044667	S2
2019 9 16	1.1004	1.1028	0.0024	0.0017067	S2
2019 9 17	1.1072	1.1045	-0.00264	-0.00504	S1
2019 9 18	1.1029	1.1039	0.0010333	0.0036733	S2
2019 9 19	1.104	1.1045	0.00053333	-0.0005	S1
2019 9 20	1.1019	1.1027	0.00089	0.00035667	S2
2019 9 23	1.0993	1.0995	0.00019333	-0.00069667	S1
2019 9 24	1.102	1.1009	-0.00107	-0.0012633	S1
2019 9 25	1.0942	1.0967	0.0025433	0.0036133	S2
2019 9 26	1.092	1.0932	0.00123	-0.0013133	S1
2019 9 27	1.0941	1.0935	-0.00062	-0.00185	S1
2019 9 30	1.0899	1.091	0.0011467	0.0017667	S2
2019 10 1	1.0932	1.0918	-0.0013867	-0.0025333	S1
2019 10 2	1.0959	1.0942	-0.00168	-0.00029333	S1
2019 10 3	1.0963	1.0968	0.00044333	0.0021233	S2
2019 10 4	1.0978	1.0977	-1.67E-05	-0.00046	S1
2019 10 7	1.097	1.0977	0.00073667	0.00075333	S2
2019 10 8	1.0956	1.0964	0.00085667	0.00012	S2
2019 10 9	1.0971	1.097	-5.67E-05	-0.00091333	S1
2019 10 10	1.1005	1.1003	-0.00027333	-0.00021667	S1
2019 10 11	1.1035	1.1033	-0.00022	5.33E-05	S2
2019 10 14	1.1026	1.1027	0.00011667	0.00033667	S2
2019 10 15	1.1032	1.1023	-0.00087333	-0.00099	S1